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MODELING ASYMMETRIC VOLATILITY WITH LONG MEMORY EFFECT USING A FIGARCH ANN APPROACH: EVIDENCE FROM ANTM STOCK

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Abstract: This study models the volatility of daily returns for PT Aneka Tambang Tbk (ANTM), which exhibits volatility clustering, fat tails, asymmetry, and long memory. The analysis proceeds in two stages: (i) conditional variance modeling using FIGARCH (1, d, 1**)** to represent long-memory dynamics; and (ii) design of a FIGARCH ANN hybrid (backpropagation) to absorb residual nonlinearity/asymmetry. Preprocessing tests confirm stationarity in log returns, followed by ARIMA baseline selection and confirmation of conditional heteroskedasticity in the residuals. Long-memory estimation via the GPH procedure confirms statistically significant long memory (past shocks have persistent effects). Compared to GARCH (1,1) and EGARCH, FIGARCH provides a better fit because it has the smallest AIC/BIC value. Residual diagnostics for FIGARCH are clean, indicating no autocorrelation and no remaining ARCH effects the model captures the main volatility structure. Ten steps ahead forecasts show the conditional variance stabilizing, implying that shocks decay slowly (persistence) toward a relatively stable level. The ANN component trained on residuals/logvariance reduces error metrics (MSE/RMSE/MAE) compared with standalone FIGARCH, evidencing the benefit of nonlinear correction for short horizon accuracy.

Keywords: volatility; long memory; FIGARCH; ANN; asymmetry; ANTM.
2020 AMS Subject Classification: 62M10, 68T07

1. INTRODUCTION

Various studies on financial markets indicate that equity return volatility exhibits stylized facts such as volatility clustering, heavy tails, and asymmetric effects (leverage effect) which

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conceptually challenge the assumptions of normality and simple linear dynamics[1][2][3]. In the context of emerging markets, these characteristics tend to be more pronounced due to their sensitivity to external shocks, domestic policy shifts, and limited market depth. The stock of PT Aneka Tambang Tbk (ANTM) serves as a relevant case in point its performance is influenced by a combination of commoditybased factors and market sentiment, resulting in volatility patterns that are often persistent (long memory) and respond asymmetrically to positive and negative shocks[4]. This situation makes volatility modeling precision not merely an academic issue, but a practical imperative for risk management spanning from Value at Risk (VaR) measurement, to the determination of margin requirements and capital buffers, and the valuation of derivative instruments [5][6][7].

Methodologically, the ARCH/GARCH family and its extensions (EGARCH/GJR) provide a solid framework for capturing conditional heteroskedasticity and asymmetry, but they generally emphasize short term dependence [8], [9]. By contrast, FIGARCH is designed to represent long-memory behavior in volatility; however, it still relies on a linear structure that can leave higher-order nonlinear patterns and interactions in empirical data unmodeled [10].This gap motivates a hybrid approach that combines the interpretability of statistical models (FIGARCH) with the capacity of artificial neural networks (ANN, backpropagation) to model residual nonlinearity [11]. Using ANTM as a case study, the present research aims to deliver more accurate, stable, and actionable volatility estimates and forecasts for decision-makers in Indonesia's capital market, while also enriching the scholarly discourse on volatility modeling in emerging markets [12].

ANTM's stock return volatility exhibits two key features that conventional models struggle to capture simultaneously: (i) asymmetric responses to positive versus negative shocks (the leverage effect), and (ii) long run persistence (long memory) in the dynamics of the conditional variance. Asymmetric GARCH variants (EGARCH, GJR) effectively represent the response asymmetry but are generally confined to short-term dependence [13]. By contrast, FIGARCH is designed to model long memory; however, it remains a linear specification that often leaves nonlinear patterns in the residuals and does not explicitly account for asymmetry [14]. These limitations can lead to volatility mis-specification, which in turn degrades forecast accuracy and biases market risk measures (Value-at-Risk, VaR). Accordingly, the research problem is the need for an integrated modeling framework that jointly captures long memory, asymmetry, and nonlinearity in ANTM data. Specifically, this study asks whether combining FIGARCH with an artificial neural network (backpropagation) to model unexplained nonlinear/residual components can deliver meaningful improvements in volatility estimation and forecasting accuracy, as well as consistency in risk measurement, relative to benchmark models such as FIGARCH.

This study aims to design, estimate, and evaluate a FIGARCH ANN hybrid framework for modeling the volatility of ANTM stock returns that exhibits asymmetry and long memory. Specifically, the objectives are to: (i) document the stylized facts of ANTM returns including volatility clustering, fat tails, and asymmetry as the empirical basis for modelling, (ii) identify and estimate the FIGARCH specification that best represents long-run dependence in the conditional variance, (iii) build an artificial neural network (backpropagation) component to capture nonlinear residuals and higher-order interactions not accommodated by FIGARCH's linear structure; (iv) integrate the two components into a coherent FIGARCH ANN model and set out reproducible estimation and validation procedures, (v) compare the hybrid model's in sample and out of sample performance against benchmarks FIGARCH using volatility forecast accuracy metrics (MSE/RMSE/MAE).

Although the volatility literature in Indonesia's capital market is expanding, substantive gaps still hinder accurate modeling for commodity sensitive stocks such as ANTM. First**,** most studies emphasize asymmetric GARCH families to capture the leverage effect but generally overlook the long-run dependence (long memory) empirically observed in the conditional variance. Second, work adopting FIGARCH does address long memory, yet typically retains a linear structure that leaves nonlinear dynamics and higher-order interactions in the residuals, and it rarely formalizes asymmetry explicitly. Third, hybrid approaches that integrate FIGARCH with artificial neural networks (ANN) remain scarce particularly in the context of emerging markets and single-name studies of ANTM, which face commodity regime shifts and domestic policy changes. As a result, comprehensive evidence is still lacking that a framework combining statistical interpretability (FIGARCH) with nonlinear flexibility (ANN) can consistently improve the accuracy of volatility estimates and the reliability of risk measurements for ANTM.

Novelty. The contribution of this study lies in a FIGARCH ANN hybrid architecture that simultaneously represents long memory, captures asymmetry (the leverage effect), and models subtle nonlinearities in ANTM's return volatility. Unlike asymmetric GARCH variants that are primarily oriented toward short term dependence or linear, standalone FIGARCH, we implement a residual learning scheme: FIGARCH first approximates the long memory component, after which ANN acts as a directed nonlinear corrector using signed predictors (positive/negative shocks), shock magnitudes, and regime indicators to explicitly formalize asymmetry that is often overlooked. Practically, the research is well motivated improving volatility model accuracy reduces risk-measurement bias, enhances margin and capital buffer setting, and supports derivatives pricing in Indonesia's commodity sensitive market. Scientifically, evidence on a commodity issuer in an emerging-market context enriches the volatility literature by offering a framework that no longer treats long memory, asymmetry, and nonlinearity as separate issues, while providing a replicable design for similar assets.

2. PRELIMINARIES

Volatility is a statistical measure describing the dispersion or variability of an asset's or market index's returns, directly reflecting the level of risk inherent in price movements in financial markets. The volatility of financial data often exhibits complex and hard to predict behavior, which adds uncertainty to financial time-series analysis. The nonstationarity and heteroskedasticity inherent in volatility therefore require models that can adaptively and accurately capture the dynamics of changing volatility. In the context of precious-metal assets such as gold, return volatility is a crucial factor in investment decision making, as sizable price fluctuations can directly affect portfolio risk management. The results of this study align with prior evidence identifying volatility as a core characteristic and key determinant of precious-metal return behavior; accordingly, a deeper understanding of volatility patterns and dynamics can enhance the effectiveness of investment strategies and risk management policies. Thus, volatility analysis not only enriches the finance literature but also provides practical value to investors and portfolio managers confronting market uncertainty

In financial time-series analysis featuring volatility, variance modeling is a primary step for effectively capturing the dynamics of changing variability. However, before modeling the variance, an essential preliminary stage is to specify the series' mean, typically using an Autoregressive Moving Average (ARMA) model. The ARMA order that is, the number of lags in the autoregressive (AR) and moving-average (MA) components is determined from the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF), which are the principal diagnostic tools for selecting an appropriate specification. Autocorrelation describes the correlation between observations in a time series at specific time intervals (lags), and the ACF is the collection of these correlations across lags. This function helps identify patterns of short and long run dependence in the data. while, partial autocorrelation measures the direct correlation between observations at a given lag after removing the influence of intervening lags, thereby providing a more specific view of the direct relationships among observations in the time series. The partial autocorrelation function (PACF) is the collection of these partial correlations across lags and likewise serves as a guide for selecting the most appropriate ARMA model structure. Accordingly, a properly specified ARMA mean model provides a solid foundation before proceeding to volatility modeling with variance models such as GARCH and its extensions.

GARCH

To understand the dynamics of stock-return volatility, this study begins by modeling with ARCH (Autoregressive Conditional Heteroskedasticity) and GARCH (Generalized ARCH). The ARCH model, first introduced by Engle (1982), captures time-varying, heteroskedastic variance in financial time series. However, its limited ability to explain persistent volatility motivated the development of GARCH by Bollerslev (1986), which more efficiently accommodates dependence of volatility on past periods. The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) framework extends the original ARCH model proposed by Engle and has proven effective for financial data that exhibit time varying heteroskedasticity.

To address heteroskedasticity, the ARCH(r) model was introduced, which incorporates the influence of past a_{t-1}^2 on the current conditional variance σ_t^2. In general, the ARCH specification is formulated as follows

$$\sigma_t^2 = \omega + \sum_{i=1}^{r} \varphi_i a_{t-i}^2$$

With $\omega > 0,\ \varphi_i > 0$ and $i = 1, 2, \dots, r.$

To overcome the limitation of the ARCH model which often requires a very high order to capture volatility fluctuations adequately Bollerslev (1986) proposed an extension via the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) framework. GARCH introduces a more efficient mechanism by incorporating the previous period's conditional variance, enabling more accurate and parsimonious volatility modeling without substantially increasing the model order. Consequently, GARCH can capture volatility clustering in financial data more effectively than the conventional ARCH model. The conditional variance in a GARCH (r, s) model is influenced not only by lagged squared residuals a_{t-i}^2 but also by lagged conditional variances σ_{t-j}^2. In general, the GARCH (r, s) model is specified as follows:

$$\sigma_t^2 = \omega + \sum_{i=1}^{r} \varphi_i a_{t-i}^2 + \sum_{j=1}^{s} \beta_i \sigma_{t-j}^2$$

With $\beta_i > 0$, dan $j = 1, 2, \dots, s$

The exponential asymmetric GARCH or EGARCH model was introduced by Nelson (1991). One problem with the standard GARCH model is the need to ensure that all estimated coefficients are positive. Nelson (1991) proposed a model that does not require nonnegativity. The following is the EGARCH equation[15]:

$$\ln(\sigma_t^2) = \lambda_0 + \sum_{i=1}^{s} \lambda_i \left|\frac{u_{t-i}}{\sigma_{t-i}}\right| + \sum_{k=1}^{n} \varphi_k \left(\frac{u_{t-k}}{\sigma_{t-k}}\right) + \sum_{j=1}^{r} \gamma_i \ln\left(\sigma_{t-j}^2\right)$$

Where φ_k is the leverage effect coefficient. If $\frac{u_{t-k}}{\sigma_{t-k}}$ is positive, the shock effect on the conditional log variance is $\lambda_i + \varphi_k$. If $\frac{u_{t-k}}{\sigma_{t-k}}$ negative, the shock effect on the conditional log variance is $\lambda_i - \varphi_k$. In the next step, the long-memory effect was measured using the FIGARCH model. In the performance evaluation section, we compared the EGARCH (asymmetric) model with the FIGARCH model and the hybrid model, FIGARCH ANN. The EGARCH model showed asymmetry through the leverage parameter and distinguished the magnitude effect from the direction of the shock, which increased the credibility of the volatility findings.

Estimation of the FIGARCH (Fractionally Integrated Generalized Autoregressive Conditional Heteroskedasticity) model is a crucial step in this study for examining the long-run dynamics of return volatility. FIGARCH is selected for its ability to capture long memory effects that frequently arise in financial market volatility but are not optimally accommodated by conventional GARCH models. By applying this specification, we aim to obtain a deeper understanding of persistent volatility dependence and the role of past shocks in shaping current stock-price variability. At this stage, FIGARCH parameters are estimated via Maximum Likelihood Estimation (MLE) using stock return data that have undergone preprocessing and stationarity verification. The estimation is complemented by diagnostic tests to ensure model adequacy and the validity of the results. Through this procedure, the study seeks to provide a meaningful empirical contribution to the literature on financial volatility modeling, particularly in the context of the Indonesian equity market.

According to prior studies, the FIGARCH (p, d, q) model is mathematically formulated to accommodate the long memory property in financial time-series volatility. It extends the traditional GARCH framework by introducing a fractional integration component, which allows the degree of differencing in volatility to be fractional (d), thereby providing greater flexibility in capturing persistent volatility dynamics. Formally, the FIGARCH (p, d, q) specification can be expressed as follows:

$$\phi(L)(1-L)^d\varepsilon_t^2 = \omega + [1-\beta(L)]v_t$$

An alternative representation of this model can be expressed by the following equation:

$$\sigma_t^2 = \omega + [1-\beta(L)]^{-1}\phi(L)(1-L)^d\varepsilon_t^2$$

$$\sigma_t^2 = \omega + \lambda(L)\sigma_t^2$$

Where $\lambda(L) = \lambda_1 L + \lambda_2 L^2 - \cdots - \lambda_q L^q$, for $0 < d < 1$ the FIGARCH model implies long-memory behaviour i.e., the impact of volatility shocks decays slowly. Moreover, note that this class of processes is not covariance-stationary**,** but is strictly stationary and ergodic for $d\epsilon[0,1]$**.** The long memory component can be factorized with the autoregressive as follows:

$$[1+\beta(L)] = \phi(L)(1-L)^d.$$

The forecasting quality of volatility models such as FIGARCH and GARCH is typically evaluated using objective and comprehensive prediction error metrics, including Root Mean Squared Error (RMSE)**,** Mean Absolute Error (MAE)**,** and Mean Absolute Percentage Error (MAPE)**.** RMSE measures the square root of the average squared difference between observed and predicted values, thereby imposing greater penalties on large errors and making it highly sensitive to outliers. MAE computes the average absolute difference between observations and predictions, providing a direct indication of error magnitude irrespective of sign. MAPE assesses the mean absolute percentage error relative to the observed values, allowing errors to be interpreted proportionally and facilitating comparisons across models with different data scales. Taken together, these three metrics offer a comprehensive picture of model accuracy, where lower values indicate superior forecasting performance and greater consistency in representing market-volatility dynamics. Accordingly, the choice of an optimal volatility model is often based on comparing the RMSE, MAE, and MAPE obtained during the forecasting evaluation.

3. MAIN RESULTS

3.1 DATA DESCRIPTION

The data used is daily stock data for PT Aneka Tambang Tbk (ANTM) from January 1, 2014 to December 30, 2024, with a total of 2668 data points. The original plot reflects a combination of trends and volatility that fluctuate over time. The description provides an initial overview of price movements that are important to consider before modeling. The following shows the daily data plot for ANTM shares.

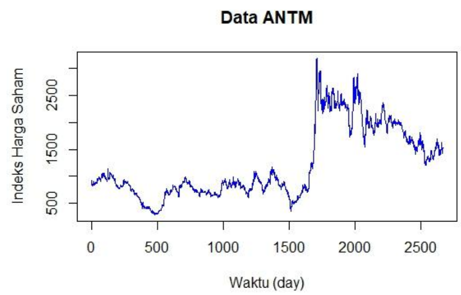

Figure 1. Daily time series of ANTM stock price index

The ANTM plot shows unstable movements over time, beginning with relatively low volatility at the start of the sample period, followed by a sharp spike around 2020-2021. Significant price changes indicate that volatility is not constant. This pattern indicates that the data does not meet the stationarity assumption. This can also be proven using the ADF test, which shows a Dickey Fuller statistic of 2.4392 with an order lag of 13 and a p-value = 0.3924. With the null hypothesis of a unit root (non-stationary series**)** and the alternative hypothesis of a stationary series**,** the p-value is greater than 0.05 at significance level of 5%. This indicates that H_0 cannot be rejected, and thus the data is non stationary based on this ADF test.

Next, the daily price data is converted into daily returns using a transformation that serves to eliminate trends, stabilize the scale, and produce data that is more suitable for volatility analysis. After the transformation, the return data is visualized to assess dispersion and indications of volatility clustering. Then, an Augmented Dickey Fuller (ADF) test is performed on the return data to test for unit roots. The following figure presents a plot of the return data.

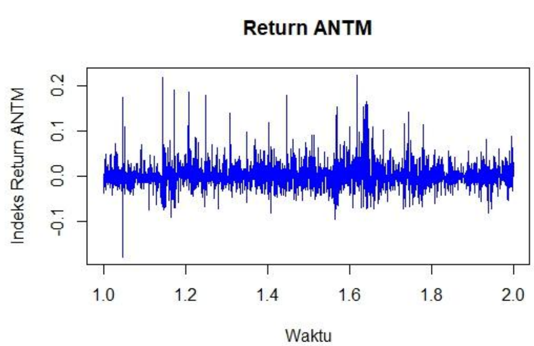

Figure 2. Daily return time series of ANTM stock

After transformation (return), the pattern fluctuates around zero, implying stationarity in the mean, but changes in interperiod variance indicate conditional heteroscedasticity. This indicates the possibility of ARCH/GARCH effect**s** and potential long memory in variance dynamics. Therefore, appropriate modeling should use the GARCH model family and, if long memory in volatility is proven, FIGARCH modeling can be considered**.** This can also be proven using the ADF test**,** which shows a Dickey Fuller statistic of -13.123 with an order lag of 13 and a p-value = 0.01. With the null hypothesis of a unit root (nonstationary series**)** and the alternative hypothesis of a stationary series**,** the p-value is greater than 0.05 at significance level 5%. This indicates that H_0 is rejected, and thus the return data is stationary.

Next, a Box-Cox test was conducted to examine the stationarity of the variance. The analysis resulted in a Box-Cox test value of 1, meaning that the data had stable variance, so transformation was not necessary.

3.2 ARIMA MODEL

The Autoregressive Integrated Moving Average (ARIMA) model was selected by examining the patterns in the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). These two graphs were used as the main diagnostic tools to infer the most appropriate order of the autoregressive (AR) and moving average (MA) components. The results of the ACF and PACF visualization of the data are presented in the following figure.

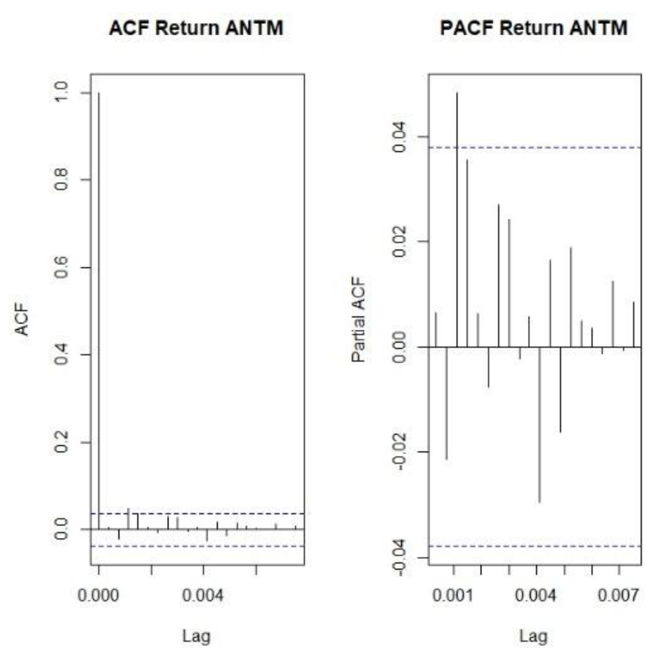

Figure 3. Sample ACF and PACF of ANTM daily log returns

From the ACF and PACF figures above, it can be concluded that the ACF is significant at lag-1, while the PACF is significant at lag-3, so that the following ARIMA models can be formed: ARIMA(1,1,0), ARIMA(1,1,1), ARIMA(1,1,3), ARIMA(3,1,0), ARIMA(3,1,1). Next, determine the best model selected from the models with the smallest AIC value.

Table 1. Comparison of fitted ARIMA models

No	ARIMA Model	AIC Value
1	ARIMA (1,1,0)	-11308.91
2	ARIMA (1,1,1)	-11306.91
3	ARIMA (1,1,2)	-11307.74
4	ARIMA (1,1,3)	-11313.52
5	ARIMA (2,1,0)	-11308.13
6	ARIMA (2,1,1)	-11307.86
7	ARIMA (2,1,2)	-11308.98
8	ARIMA (2,1,3)	-11311.56
9	ARIMA (3,1,0)	-11312.42
10	ARIMA (3,1,1)	-11313.91
11	ARIMA (3,1,2)	-11311.9
12	ARIMA (3,1,3)	-11312.08

Based on the comparison of the smallest AIC values, the best ARIMA model selected is ARIMA (3,1,1) with an AIC value of -11313.91. The results of the ARIMA (3,1,1) model estimation on returns. The estimation produces coefficients AR (1) = 0.5975 (s.e. 0.2358), AR (2) =−0.0258 (s.e. 0.0226), AR (3) =0.0615 (s.e. 0.0200), and MA (1) =−0.5919 (s.e. 0.2363).

Diagnostic Tests

a. Heteroscedasticity test

The results of the ARCH heteroscedasticity test on the residuals indicate strong conditional volatility. The Portmanteau–Q on the residual squares produces very large statistics at various orders with p-values close to zero, thus rejecting the null hypothesis of homoscedasticity and supporting the alternative of heteroscedasticity. This finding indicates the presence of an ARCH effect on the ARIMA (3,1,1) residuals. This is reinforced by the results of the Lagrange Multiplier (LM) test on the residuals**,** which show very strong evidence of conditional heteroscedasticity. The LM statistics are very large at various orders, namely LM(4)=4992 ($p \approx 0$), LM(8)=2208 ($p \approx 0$), LM(12)=1381 ($p \approx 0$), LM(16)=1020 ($p \approx 0$), LM(20)=806 ($p \approx 0$), and LM(24)=662 ($p \approx 0$)

b. Autocorrelation test

Q* = 586.91 is the Ljung-Box test statistic value with df = 529, p-value = 0.04097 (α = 5% p-value < 0.05), so reject H_0. This means that there is still significant autocorrelation in the residuals. In other words, the ARIMA (3,0,1) model has not captured all the patterns in the data the residuals are not completely white noise.

c. Normality test

The test statistic W = 0.90007 (close to 1 means more normal). The p-value is < 2.2e-16, which is very small and less than 0.05, so reject H_0 that the residuals are not normal. Since they are not normally distributed, the ARCH/GARCH model is better to use.

3.3 GARCH MODEL

ACF and PACF of ARIMA (3,1,1) residuals

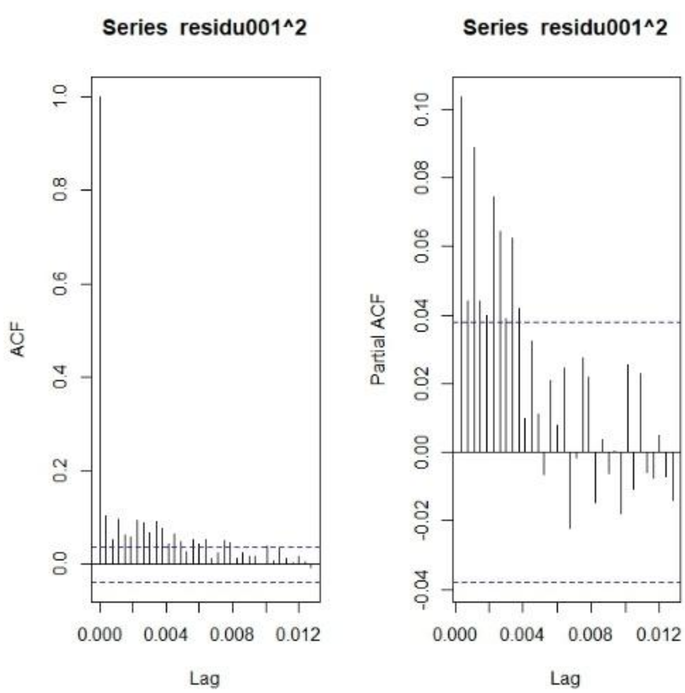

Figure 4. ACF and PACF of squared residuals of ANTM daily returns

The figure shows that the ACF is significant at Lag-1, while the PACF is significant at Lag-1, Lag-2, and Lag-3. Thus, the following ARCH models can be formed: ARCH (1,0), ARCH (1,1), ARCH (1,2), ARCH (1,3). The best ARCH model is selected by comparing the smallest AIC and BIC values. The following is the ARCH model estimation.

Table 2. Comparison of fitted ARCH models

No	ARCH Model	AIC Value	BIC Value
1	ARCH (1,0)	-4.276118	-4.271702
2	ARCH (1,1)	-4.373987	-4.367363
3	ARCH (1,2)	-4.374301	-4.365469
4	ARCH (1,3)	-4.373618	-4.362578
5	ARCH (2,0)	-4.293631	-4.287007
6	ARCH (2,1)	-4.373803	-4.364971
7	ARCH (2,2)	-4.374034	-4.362994
8	ARCH (2,3)	-4.373316	-4.360068
9	ARCH (3,0)	-4.338219	-4.329387
10	ARCH (3,1)	-4.378693	-4.367653
11	ARCH (3,2)	-4.380046	-4.366798
12	ARCH (3,3)	-4.382843	-4.367387

The ARCH (3,3) model has the smallest AIC and BIC values. However, the ARCH (1,1) model can also be used for a stable model. The GARCH (1,1) estimation results for ANTM returns show that all main parameters are significant and volatility dynamics are very persistent. The constant value (ω) = 4.387×10^{-5}, ARCH (α_1) = 0.09586, GARCH (β_1) = 0.8567.

3.4 LONG MEMORY TEST AND FIGARCH MODEL

Before modeling long-memory, we first estimated EGARCH (1,1) as an asymmetric parametric baseline. The estimation results show that the parameter $\alpha = 0.1217$ is significant and positive, which means that stock price volatility is sensitive to the magnitude of shocks in the previous period. The positive value of $\gamma = 0.2441$ indicates a positive asymmetry effect, where price increases (positive returns) actually increase volatility more than price decreases. Meanwhile, $\beta = 0.3648$ shows that the volatility effect is temporary and tends to subside quickly. Thus, the EGARCH (1,1) model is quite capable of describing the volatility dynamics and asymmetric nature of the analyzed stock returns.

Then, followed by a long memory test, the fractional differentiation parameter value obtained was d = 0.4391808. This result indicates that the volatility of ANTM stock returns has significant long memory properties, as indicated by the value of $0 < d < 0.5$ meaning that the process remains stationary. Thus, the GARCH model's, which only captures short memory, is insufficient to describe the dynamics of volatility, requiring FIGARCH modeling to accommodate the long memory effect. Based on the FIGARCH (1, d,1) modeling results, $\omega = 5.45\times10^{-5}$, $\varphi = 0.261$, $d = 0.439$, $\beta = 0.605$, and the degree of freedom $\nu = 3.54$. Advalue close to 0.5 indicates strong long memory in volatility. The following is a comparison of the garch(1,1) and figarch(1,d,1) models.

Table 3. Comparison of fitted GARCH (1,1) and FIGARCH (1, d,1)

MODEL	AIC Value	BIC value
GARCH (1,1)	-12136.17	-12112.61
EGARCH	-4.3792	-4.3593
FIGARCH (1, d,1)	-12185.47	-12156.03

The best model is the FIGARCH (1, d,1) model with the smallest AIC and BIC values. Forecasting the FIGARCH (1, d,1) model for 10 steps

Table 4. Forecasts of conditional variance for ANTM returns

NO	Data to	Forecast	NO	Data to	Forecast
1	2668	0.0009428891	6	2673	0.0009957844
2	2669	0.0010024089	7	2674	0.0009937315
3	2670	0.0010052389	8	2675	0.0009922287
4	2671	0.0010019163	9	2676	0.0009912252
5	2672	0.0009984942	10	2677	0.0009906205

The variance starts at 0.0009429, then rises slightly to 0.0010024, and stabilizes around 0.00099.

This means that FIGARCH predicts long-term persistence (long memory): the variance does not decrease quickly, but tends to remain stable. Volatility is stable around 0.0307 – 0.0317. Stable prediction longer lasting shock effect.

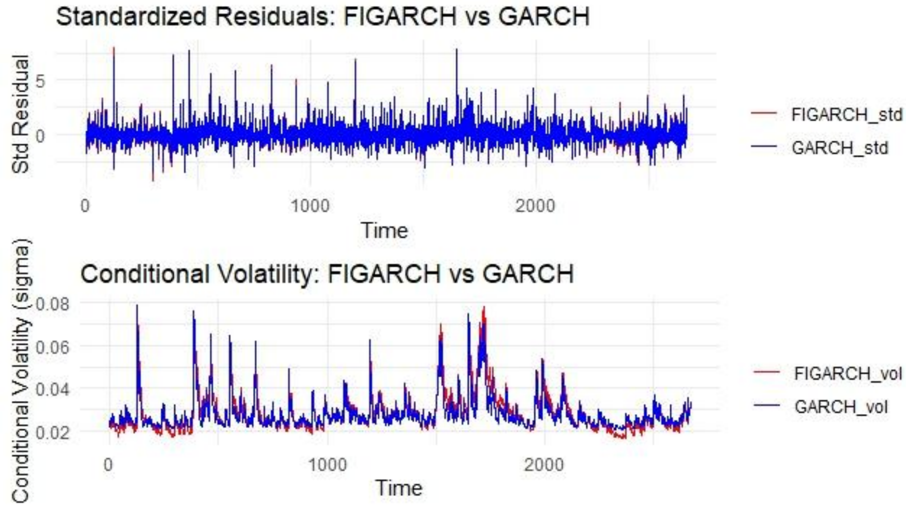

Figure 5. Comparison of FIGARCH and GARCH models on ANTM returns

3.5 FIGARCH ANN

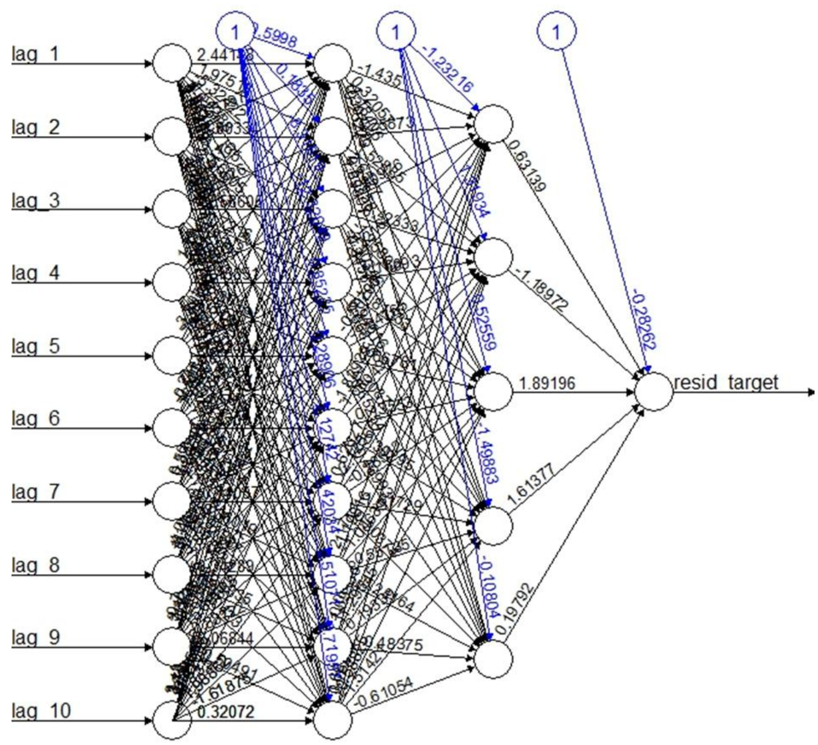

Figure 6. Neural network for nonlinear correction of FIGARCH residuals

Table 5. Comparison MSE, RMSE, and MAE of FIGARCH and FIGARCH ANN

	FIGARCH	FIGARCH ANN
MSE	1.508	0.943
RMSE	1.228	0.971
MAE	0.95	0.179

Long memory volatility gives d = 0.4391808, confirming the existence of long memory in ANTM return volatility, so that short-memory models such as conventional GARCH may be inadequate. This finding forms the basis for selecting FIGARCH to capture these long-term memory dynamics. FIGARCH (1, d, 1) estimation. The representative parameters obtained are $\omega = 5.45 \times 10 - 5$ $\beta = 0.605$ and $v = 3.54$. These values are consistent with a highly persistent (long memory) volatility process with Student-t distribution (fat tails) on the innovation. FIGARCH ANN hybrid. The paper also describes the FIGARCH–ANN design that utilizes ANN to correct non-linear patterns in FIGARCH residuals. The evaluation summary shows an improvement in metrics for the hybrid compared to the single FIGARCH.

4. CONCLUSION

ANTM volatility analysis shows long memory with FIGARCH parameter d = 0.4391808, which consistently indicates long-term persistence in return variance. Compared to GARCH (1,1), EGARCH (1,1), the FIGARCH model is more appropriate because it has a lower AIC/BIC while the RMSE is the same at 0.028958. Therefore, the selection of the FIGARCH model is also considered adequate because the residuals (no remaining autocorrelation/ARCH effect). For forecasting, the 10-step projection shows a conditional variance that converges around 0.00099, confirming persistence with a relatively controlled level of risk. Furthermore, the FIGARCH ANN hybrid proved promising: modeling the residuals with ANN reduced the MSE/MAE compared to FIGARCH alone, indicating the ability of ANN to absorb the remaining nonlinearity/asymmetry of the residuals.

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CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests.

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